CLOSED-LOOP ATTENTION MANAGEMENT: USING AUGMENTED COGNITION TO SUSTAIN VIGILANCE

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ABSTRACT

Vigilance tasks, from driving to surveillance to security remain important and frequent tasks for the US Army. Yet the difficulty users have sustaining vigilance is well known. Augmented cognition offers new methods for supporting sustained vigilance via a closed-loop attention management system (CLAM). A CLAM system monitors operators' psychophysiology for signs of inattention and then triggers a countermeasure to rouse operators and help them sustain vigilance and good task performance. Here, we report an evaluation of a complete closed-loop system composed of a combination of eye, head, and EEG measures and a novel countermeasure composed of a cognitively demanding secondary task. In order to evaluate the CLAM system, the secondary task was triggered either when inattention was detected (CLAM) or at random intervals throughout a 40 minute vigilance task. While participants in both conditions demonstrated a vigilance decrement, as measured by an increase in misses over the course of the session, the CLAM condition produced 17% fewer misses overall than the random condition. These results indicate successful real-time detection of inattention and an effective countermeasure for rousing participants and sustaining vigilance and task performance. The results inform our understanding of how human vigilance operates and the technology for its detection and manipulation.

1. INTRODUCTION

Vigilance tasks, such as video surveillance from remote vehicles, check-point security, automation supervision, and long-distance driving, remain important and frequent tasks for the US Army. Unfortunately, vigilance tasks are highly repetitive and understimulating, and operators struggle to sustain vigilance for even short stretches of time. Augmented cognition is a relative newcomer to the toolbox of methods to support sustained vigilance. The concept is to monitor operators' psychophysiology for signs of inattention and trigger a countermeasure when vigilance drops below a threshold. This concept is called a Closed-Loop Attention Management system (CLAM) because the system monitors operators' attention and then intervenes in order to sustain it at an appropriate level for good task performance.

An effective closed-loop system requires jumping a variety of technical and scientific hurdles including the development of comfortable and wireless equipment, psychophysiological measures that are sensitive to vigilance levels, methods for combining multiple measures in real-time for accurate and timely detection of inattention, and effective countermeasures to rouse the user and mitigate any vigilance decrement (St. John & Kobus, 2008). Much recent progress has been made toward addressing each of these hurdles. Our research has focused primarily on identifying combinations of measures and developing effective countermeasures. Here, we report an evaluation of a complete closed-loop system composed of a combination of eye, head, and EEG measures and a novel countermeasure composed of a cognitively demanding secondary task. The results enrich our understanding of how human vigilance operates and the technology for its detection and manipulation.

A number of psychophysiological measures have shown promise for detecting inattention either alone or in combination including EEG, eye movements, and head and body posture (e.g., Balaban et al., 2004; Duta, Alford, Wilson, & Tarassenko, 2004; Jung, Makeig, Stensmo, & Sejnowski, 1997; Van Orden, Jung, & Makeig, 2000). Recently, St. John, Risser, and Kobus (2006) found that a combination of a derived EEG measure of task engagement, percent eye closure, and variability of head pitch (nodding) predicted 42% of the variance in the miss rate during a vigilance task. Individually tailored combinations predicted from 32 to 91% of the variance.

Additionally, many countermeasures have been tested for sustaining vigilance (See, Howe, Warm, & Dember, 1995), and a few have been tested in closed-loop settings. For example, Mikulka, Scerbo, and Freeman (2002) used an EEG measure of attention during a target detection vigilance task, and when inattention was detected, the system increased the stimulus presentation rate of the primary task. Berka et al. (2005) used a different EEG measure of task engagement during a simulated driving task, and when losses in task engagement were detected, the system sounded an alarm. Both countermeasures improved primary task performance.

St. John and Risser (2007) evaluated the potential for secondary tasks to serve as vigilance countermeasures. This secondary task countermeasure was designed to meet three criteria: a) it would occur only

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occasionally so as not to annoy or tax operators' resources, b) require different cognitive processes than the vigilance task so as not to interfere with concurrent processes dedicated to the primary task, and c) be relatively interesting and engaging. Accordingly, participants heard a string of three digits presented auditorily, and they were asked whether they could be reordered to be consecutive with no gaps, for example, "1-3-2" versus "1-4-2." The digit task was repeated three times for each countermeasure. The digit task requires auditory processing and verbal working memory to store and resequence the digits, while the vigilance task requires visual processing and spatial working memory to compare the visual stimulus against the remembered target. St. John and Risser (2007) found that the digit task was as effective as an alarm, but it was rated as less annoying by participants – an important practical consideration. This 3-digit secondary task was used as the countermeasure in the current closed-loop evaluation.

To truly demonstrate the effectiveness of a closed-loop augmented cognition system, the psycho-physiologically triggered countermeasure must be more effective at sustaining vigilance than the same countermeasure triggered randomly via an open-loop. Therefore, the present study compared the closed-loop-triggered countermeasure to a randomly triggered countermeasure. Each participant performed both conditions in a counter-balanced order. This within participant design controlled for the large individual differences in both task performance and ability to sustain vigilance. We hypothesized that the closed-loop-triggered countermeasure would help sustain vigilance, and reduce misses, better than the randomly triggered counter-measure.

2. METHOD

2.1 Participants

Participants were recruited from www.craigslist.org/software-QA-DBA and the University of California, San Diego in order to find participants who were knowledgeable of computers and high tech equipment. Participants were further screened for a good knowledge of English and having or being in the process of obtaining a bachelor degree. Twenty-eight people participated in the study. Ten people were excluded for a variety of reasons: four people failed to pass the EEG baseline tasks due to equipment problems or unusual EEG patterns, four people had incomplete eye tracking data due to excessive body motion or unusual interference from their glasses, and two people failed to pass the training criterion for the primary vigilance task.

For the 18 people who completed the experiment and are included in the analysis, there were 10 males and eight females, and the mean age was 32, ranging from 19 to 59. Participants reported getting slightly over seven hours of sleep per night on average, and all participants scored normally ($\leq$ 10) on the Epworth Sleepiness Scale (Johns, 1992), indicating that no participants were sleep deprived or had sleep disorders that might affect the EEG or vigilance task results.

The experiment lasted approximately four hours, from 10am to 2pm in order to obtain EEG baseline measures in the morning and conduct the vigilance study in the early afternoon. Participants were paid $60 and provided lunch.

2.2 Apparatus

A SmartEye Pro desktop eye tracking system, version 4.5.4, was used to record head movement and percent eye closure. The system includes two 60 Hz cameras located on either side of the computer monitor that allowed the participant to move freely with minimal data loss. For each participant, a unique head model was created by marking facial features that allowed the system to track each individual. Head pitch was measured as a rotation around the X axis (through the ears). Head pitch variability (nodding) was computed as the standard deviation of head pitch over a 60 second window. Percent eye closure was measured as the vertical distance between the upper and lower eyelids. It was made relative to each participant by computing it as a percentage deviation from a baseline open eye average. The open eye average was obtained during an early training session when participants were alert and engaged in learning the vigilance task. The head and eye data were cleaned in real-time by discarding data when the system could not find the head and at least one eye.

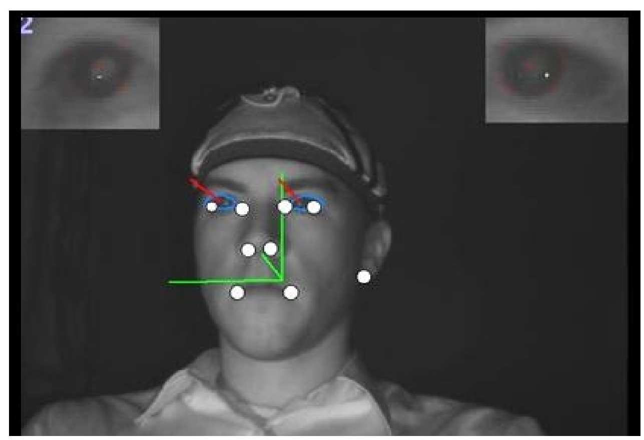


Figure 1. Illustration of eye, head, and EEG tracking. The percent eye closure measure is illustrated by the circles around the eyes, head pitch is illustrated by the 3D coordinates centered on the face, and the head cap is used to acquire EEG.

A B-Alert wireless EEG system was used to acquire bipolar recordings at 256 Hz from Fz-POz and Cz-POz and unipolar recordings from Fz, Cz and POz referenced to linked mastoids. The B-Alert system automatically identified and removed eye blink and EMG artifacts. Prior to the experimental sessions, a series of B-Alert baseline tasks modeled each participant's EEG profile. Using a discriminant function analysis of the EEG spectrogram, each one-second EEG epoch was classified along a task engagement scale by computing the probability that the EEG data fell within each of four levels of engagement: high engagement (HE), low engagement (LE), relaxed wakefulness (predominance of alpha), or sleepy (predominance of theta; Berka et al., 2007).

In the CLAM condition, percent eye closure, head pitch variability, and LE were collated in real-time using custom software. The data were polled every two seconds for the most recent value of each measure, then a mean was computed for each measure for the prior 60 seconds. The measure of inattention, called the predicted miss rate, was computed by multiplying each measure by a weight and adding a constant. The values for the weights and the constant were computed from data obtained from nine participants performing the identical vigilance task without any countermeasures (St. John, Risser, & Kobus, 2006). The countermeasure was triggered when the predicted miss rated exceeded 0.5. This trigger threshold was set through pilot testing. The countermeasure was also triggered if the predicted miss rate could not be computed for 60 consecutive seconds, typically because the participant fell out of view of the eye tracker. Once triggered, the countermeasure could not be triggered again for 60 seconds. This period provided time for the countermeasure to be presented and for it to take an effect on participants' vigilance level.

In the random condition, the countermeasure was triggered on a pseudorandom schedule with an interval of 120 seconds plus a random deviation between -30 and 30 seconds. Consequently, the countermeasure was triggered 19 or 20 times per session. The interval was set through pilot testing to roughly match the average number of countermeasures occurring in the CLAM condition.

2.3 Task and Stimuli

Participants performed a 40 minute vigilance task that was couched as a UAV surveillance task, monitoring a simulated video feed taken from a UAV flying along a highway (St. John, Risser, & Kobus, 2006). Participants were asked to monitor the highway for long-bed trucks because local insurgents were known to use long-bed trucks for subversive activities (see Figure 2). In these respects, the task was more visually complex than typical vigilance tasks, but it maintained the essential characteristics of a vigilance task (See, Howe, Warm, & Dember, 1995).

The target trucks had 10% longer beds (110 pixels) than the distracter trucks (100 pixels). One truck appeared every two seconds for 400ms at one of six locations along a vertically oriented road displayed on a 17" LCD monitor set at a resolution of 1024 x 768 pixels. Participants were seated at arm's length from the monitor. Three targets appeared per minute and were presented randomly and nonconsecutively among 27 distracters, a target rate of 1 in 10. Participants responded to targets by pressing the space bar. No feedback was provided. A miss was logged if a participant failed to respond to a target within two seconds of target onset. Hits, misses, false alarms, and response times were recorded for each trial.

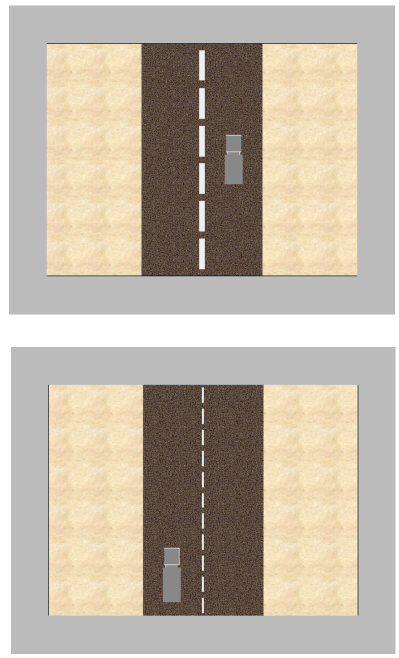


Figure 2. Screenshots of the vigilance task. Long and short-bed trucks appeared briefly at six locations along the road; (top) a distracter short-bed truck, (bottom) a target long-bed truck.

The countermeasure was the 3-digit secondary task described above. Participants responded by pressing the left and right arrow keys. A miss was logged if a participant failed to respond within 3.5 seconds of the auditory offset. Auditory feedback was provided for correct and incorrect responses. Each countermeasure consisted of three trials, that is, three sets of digits. The total time for the three trials, including time for participants' responses, was about 18 seconds.

2.4 Procedure

After signing consent forms, participants were prepped and fitted with the B-Alert EEG cap. They performed a series of three five-minute B-Alert baseline tasks to derive their unique EEG profile. Next, their head model was created with the eye tracking system by marking participants' facial features in the software. Participants were then introduced to the vigilance task. First, participants completed a two minute demonstration trial with auditory feedback and a target rate higher than that used during the experimental task (1 in 3). Second, participants completed a three minute practice trial with auditory feedback, but with the target ratio the same as it would be during the experimental task (1 in 10). Participants repeated this trial until they reached criterion performance of three or fewer errors (misses or false alarms). Participants who failed to reach the criterion after four tries were dismissed.

Third, participants were provided a 30 minute lunch. Fourth, following the lunch break, participants were reacquainted with the vigilance task with another three minute trial. They were not required to meet the criterion again. Fifth, the secondary task was described, and participants practiced for 10 trials with feedback. Sixth, the vigilance task and the secondary task were then combined for a final three minute practice trial. During this trial, the secondary task occurred on a fixed schedule so that all participants received equal experience. Feedback was provided for both tasks.

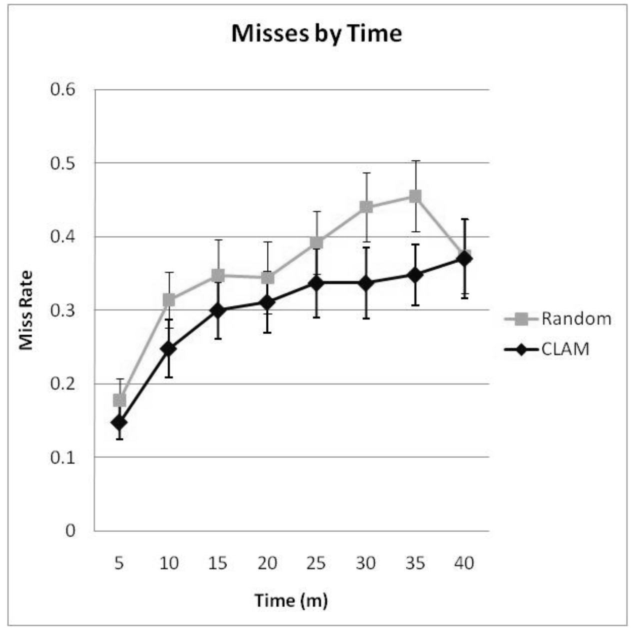
Finally, participants received two sessions of the experimental task, once in the CLAM condition and once in the random condition. The conditions occurred in a counterbalanced order. Participants were told there were two control procedures for triggering the countermeasure, and we were testing which one worked better. They were not told which procedure was which, and EEG, head, and eye data were recorded for both sessions. Feedback was provided only for the secondary task. Each session lasted 40 minutes. Participants received a short break between sessions and were instructed to walk around the building for five minutes. Before starting the next session, the participant was re-trained with the three minute vigilance task and the three minutes of combined vigilance and secondary task, with feedback, to establish the same level of training going into each experiment session.

3. RESULTS AND DISCUSSION

The primary hypothesis of the experiment was that CLAM control over the countermeasure trigger would sustain vigilance and task performance better than random control over the countermeasure trigger because the CLAM system would tailor the countermeasure to occur specifically when participants were inattentive and the countermeasure was most needed. To test this hypothesis, as well as examine the time course of performance, each participant's miss rate was computed in five-minute consecutive blocks across the 40-minute session (see figure 3).

The five minute data were submitted to a repeated measures ANOVA with condition (CLAM or random) and block as repeated factors and order of sessions as a between factor. The effect of condition was significant, $F(1,16) = 5.3$, $p = .035$. CLAM control over the countermeasure led to fewer misses than random control. Across all eight blocks (40 minutes) the average rate of misses under CLAM control was 0.30, and the average rate of misses under random control was 0.36. Therefore, CLAM improved the miss rate by 17%.

The effect of block was also significant, $F(7, 112) = 9.3$, $p < .0001$. The miss rate in both conditions followed the classic vigilance decrement pattern, with a sharp increase in the miss rate during the first 10 to 15 minutes of a session, followed by a more subtle increase or steady state. The order of conditions was not significant, $F(1, 16) = .91$. There was no reliable difference in response times to detected targets for the two conditions.



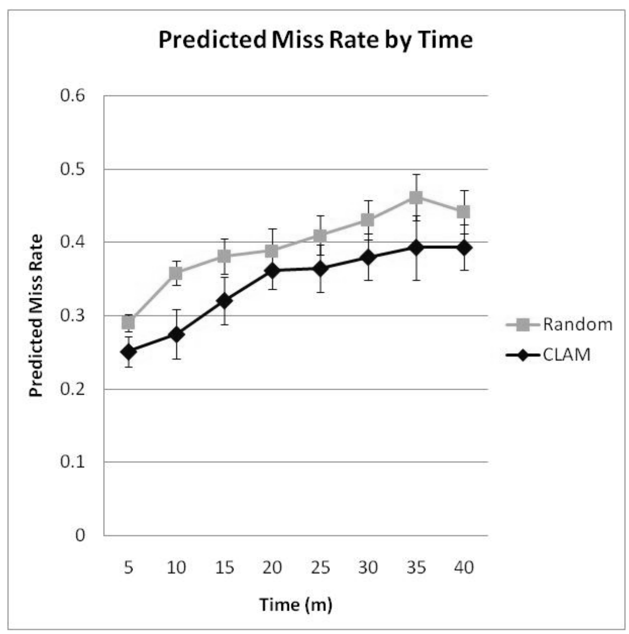


Figure 3. The time course of misses (top) and the time course of the predicted miss rate (bottom) across each 40 minute session.

The predicted miss rate also showed a significant difference between conditions $F(1,15) = 9.0$, $p = .009$. The number of participants in this analysis was reduced by 1 because one participant was out of view of the eye tracker for one block, and no predicted miss rate could be computed for that block. While participants were in the random condition, they were immediately and consistently less vigilant than they were in the CLAM condition.

Following both sessions, participants were asked several questions about their subjective experiences. Thirteen out of 18 participants (72%) reported that they performed better in the CLAM condition than in the random condition, $p = .0002$ by a one-sample sign test. These 13 participants did in fact show a greater benefit from CLAM (18%) than the other five participants (8%), but the different in the benefits was not significant, $F(1,16) = .37$. A somewhat different set of 13 out of 18 participants (72%) reported the CLAM condition provided better-timed countermeasures than the random condition. These participants also showed a greater benefit from CLAM (19%) than the other five participants (10%), but the difference in benefits was not significant, $F(1,16) = .10$.

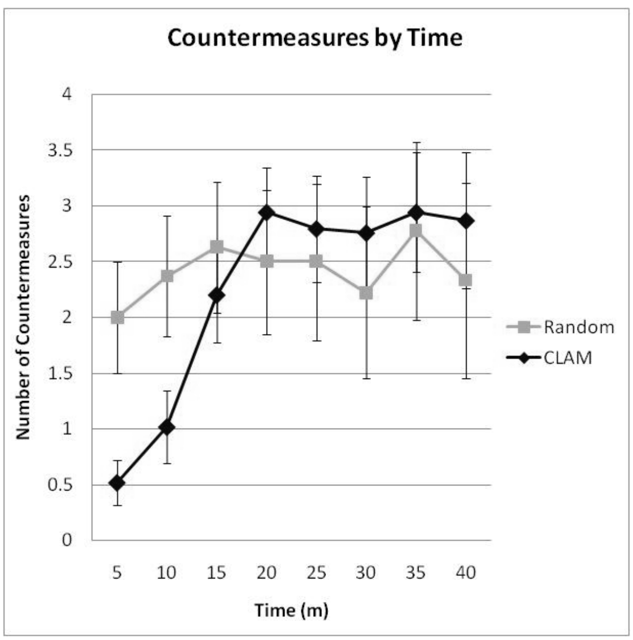


Figure 4. The time course of countermeasures between the CLAM and random conditions across the 40-minute vigilance task.

The countermeasure was triggered an average of 18 times in the CLAM condition and 19 times in the random condition. This similarity means that the benefits of CLAM were not due to differences in countermeasure presentation rates between the two conditions.

While the number of countermeasures did not vary across conditions, their time course did vary. The interaction between block and condition was significant, $F(7, 112) = 13.7$, $p < .0001$. As shown in Figure 4, the number of countermeasures per five minute block in the random condition held fairly constant across the session, in accord with the uniform random distribution that triggered the countermeasures. The number of countermeasures per five minute block in the CLAM condition, however, started low and increased sharply across the session, in accord with the predicted miss rate and task performance. This distribution demonstrates the tailoring of the closed-loop countermeasure schedule to participants' levels of inattention.

CONCLUSIONS

The UAV vigilance task is quite difficult. Even in the CLAM condition, participants missed 30% of the targets. Nonetheless, the 17% improvement over the random condition represents a substantial improvement. This improvement is especially impressive since the random condition contained the same type and number of countermeasures as the CLAM condition. Therefore, the improvement is not due to the countermeasures, *per se*, but rather to tailoring the timing of the countermeasures to participants' detected levels of inattention.

Consequently, these results constitute strong support for the closed-loop attention management concept. Achieving this improvement required sophisticated engineering and application of neurocognitive theory: the individual psychophysiological measures of inattention, their real-time collation, the computation of the trigger, and the design of the countermeasure.

Nonetheless, the components of the closed-loop can be improved. While the individual measures are well established, the method for combining the measures to compute the trigger, and the countermeasure, itself, are much more experimental. Further research in both of these areas is warranted.

For example, the trigger computation currently uses a generic function for all participants. The individual measures are combined in a linear equation, and the weights in the equation were derived from a set of nine participants from a prior study (St. John, Risser, & Kobus, 2006). It is clear from that study, however, that there are large differences in how well each psychophysiological measure predicts inattention for a given individual. Tailoring the linear equation in the trigger computation for each individual is likely to improve the detection of inattention and, in turn, the timing of triggers, and result in better sustained vigilance.

This individual tailoring of the weights in the trigger computation would be derived from performance on the vigilance task itself, in a baseline condition with no countermeasures. Each participant would first perform the vigilance task with no countermeasures. The values of the psychophysiological measures would then be regressed against that participant's vigilance task performance. This regression would determine individually tailored weights for that participant for how the psychophysiological measures predict misses and inattention. Those weights would then be transferred to the trigger computation for that participant. Finally, the participant would performance the vigilance task again with the individually tailored trigger computation to drive the countermeasures.

Another area for improvement is the countermeasure. The goal is a countermeasure that reengages participants in the vigilance task rather than distracts them, overburdens them, or annoys them. The current countermeasure was designed to draw on different mental processes than the vigilance task to minimize distraction and resource overload. Our assumption, which appears to have been validated, was that requiring the use of mental resources and processes that are distinct from the processes required of the vigilance task would re-engage participants. Still, it would be worthwhile to explore which dimensions of the secondary task are most effective for re-engaging participants, for example, variety of mental processes, variety of external stimulation, level of difficulty and challenge, intermittency, novelty, and even intrinsic or hedonistic interest (Jordan, 2000).

Finally, it is intriguing and theoretically significant that adding a secondary task as a countermeasure increases vigilance task performance. Recent research has documented that vigilance tasks are stressful and workload increases as participants struggle to remain vigilant (Grier, Warm, Dember, Matthews, Galinsky, & Parasuraman, 2003). Similarly, resource theories suggest that the vigilance decrement occurs as resources are drained and not replenished (Warm, Dember, & Hancock, 1996; Wickens, 1991). Nonetheless, we found here that adding an occasional secondary task can sustain vigilance and task performance (see also St. John & Risser, 2007). These results suggest that the extra stimulation and task demands of the secondary task actually replenish resources broadly, perhaps by a generalized activation of resources in the brain, to both support the secondary task as well as reengage participants with the vigilance task.

As discussed above, it is not yet clear what dimensions of the secondary task replenish resources and sustain attention rather than drain resources further. It is also not clear what mechanism is responsible, though it is clear that it is not a zero-sum game – secondary task demands can, in some circumstances, increase resources rather than diminish them.

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